OBESITY AND NUTRIENT CONSUMPTION: A RATIONAL ADDICTION?

TIMOTHY J. RICHARDS, PAUL M. PATTERSON, and ABEBAYEHU TEGENE*

Recent research shows that the dramatic rise in obesity in the United States is due more to the overconsumption of unhealthy foods than underactivity. This study tests for an addiction to food nutrients as a potential explanation for the apparent excessive consumption. A random coefficients (mixed) logit model is used to test a multivariate rational addiction model. The results reveal a particularly strong addiction to carbohydrates. The implication of this finding is that price-based policies, sin taxes, or produce subsidies that change the expected future costs and benefits of consuming carbohydrate-intensive foods may be effective in controlling excessive nutrient intake. (*JEL* D120, I120, C230)

I. INTRODUCTION

The Surgeon General estimates the annual direct and indirect costs of obesity at approximately \$117 billion. Clearly, the search for an appropriate public policy response has gone beyond a public health interest to a national economic imperative. Existing research on the economic causes of the national "obesity epidemic" cites technological changes that have reduced the price of food at the same time that burning food, or expending calories through either work or leisure activities, has become more expensive (Lakdawalla and Philipson, 2002; Philipson, 2001; Philipson and Posner, 1999), the proliferation of convenient meal solutions through fast food restaurants, the effectiveness of antismoking campaigns, greater labor market participation and engagement in low-wage jobs and lower real-food prices (Chou, Grossman, and Saffer, 2004), or individuals' propensity to become addicted to the consumption of food (Cawley, 1999). Although these studies develop comprehensive models that incorporate potential explanations from both sides of the energy balance equation (i.e., weight gain = energy in − energy out), recent evidence on aggregate energy intake relative to physical activity levels suggest that a more careful analysis of food consumption is warranted. Consequently, this study investigates whether specific macronutrients or minerals (protein, carbohydrates, fat, or sodium) are indeed addictive, and if so, whether addiction results from rational economic decisions.[1]

Cutler, Glaeser, and Shapiro (2003) cite U.S. Department of Agriculture (USDA) statistics that document a remarkable rise in the total amount of calories consumed since 1980. Further, much of this increase is attributable to a rapid rise in the consumption of refined carbohydrates, from 147 pounds per capita per year in 1980 to 200 pounds in 2000 (USDA, 2002). This trend is somewhat alarming as

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Richards: Power Professor, Morrison School of Management and Agribusiness, Arizona State University, Mesa, AZ 85212. Phone 480-727-1488, Fax 480-727-1961, E-mail trichards@asu.edu

Patterson: Professor, Morrison School of Management and Agribusiness, Arizona State University, Mesa, AZ 85212. Phone 480-727-1124, Fax 480-727-1961, E-mail paul.patterson@asu.edu

Tegene: Economist and Branch Chief, Economic Research Service, USDA, Washington, D.C. 20036-583. Phone 202-694-5527, Fax 202-694-5622, E-mail ategene@ers.usda.gov

1. Although the set of macronutrients includes only protein, carbohydrates, and fat, excessive consumption of sodium may also lead to health problems such as hypertension (high blood pressure), cirrhosis of the liver, kidney damage, stomach cancer, and heart disease (National Institutes of Health, 1998).

ABBREVIATIONS

BLP: Berry, Levinsohn, and Pakes
BMI: Body Mass Index
IIA: Independence of Irrelevant Alternatives
MSL: Simulated Maximum Likelihood
RCL: Random Coefficient (mixed) Logit
USDA: U.S. Department of Agriculture

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refined carbohydrates are a nutrient that is typically associated with obesity. Over the same period, however, calories used through both work and recreational activities have remained relatively static (Cutler, Glaeser, and Shapiro, 2003). Significantly, according to recent estimates from the Centers for Disease Control and Prevention (2004), fully 30.5% of U.S. adults were obese in 2001, and 64.5% were either overweight or obese (Flegal et al., 2002)[2] On the surface, therefore, it appears as though the obesity epidemic is largely due to not only food consumption but consumption of particular types of foods, consumption beyond the point necessary to maintain a healthy lifestyle. If consumers are rational, utility-maximizing agents as economists assume, how can their demand for food be so clearly suboptimal from a health perspective? This study is the first to test whether consumers' "rational addiction" to specific macronutrients constitutes a viable explanation for the rising incidence of obesity in the United States.

To test the rational addiction hypothesis, we use a dynamic random coefficient (mixed) logit (RCL) model similar to Erdem (1996). This approach represents a dynamic extension of the static, attribute-based RCL models used by Berry (1994), Berry, Levinsohn, and Pakes ([BLP] 1995), Nevo (2001), Chintagunta (2002), and Chintagunta, Dube, and Singh (2002) to explain the demand for differentiated products in a high-dimension discrete choice environment. RCL models convey several advantages over traditional, multilevel demand systems for problems such as this. First, they are parsimonious representations of a complex decision process. Second, they do not suffer from the "independence of irrelevant alternatives" (IIA) problem of traditional logit models, which leads to unrealistic estimates of substitutability among products. Third, viewing different products as bundles of desired attributes allows the modeler to project demand from product space into characteristics space, thus greatly reducing the number of parameters to be estimated. Fourth, RCL models are consistent with consumer utility maximization, so response parameters estimated in an RCL context are assumed to represent optimal, rational economic responses (Berry, 1994; BLP, 1995; Nevo, 2000, 2001). Further, this approach addresses critical weaknesses of existing empirical tests of the rational addiction hypothesis in that we are able to test for addiction to several nutrients at the same time, it is able to easily incorporate the effect of adjustment costs on addictiveness, and it recognizes that addiction is based on the content of products people consume and not on the products themselves.

We apply this econometric approach to a highly detailed, household-level scanner data set in which 30 families in a major U.S. metropolitan market report all food purchases over a 4-yr time period. Our focus in this study lies specifically in sample households' purchases of snack foods because of the diversity of snack foods' nutritional content, the importance of snack foods in modern American diets, the fact that they represent somewhat "discretional" or impulse purchases, and a practical necessity to focus on a narrowly defined set of foods for estimation purposes. In fact, there is much evidence to suggest that snacking is one of the primary causes of overconsumption and hence obesity (Buchholz, 2003; Food Institute, 2003; Putnam and Allshouse, 1999). Buchholz (2003) reports that in 1987–1988, the typical American snacked less than once per day; by 1994, they were snacking 1.6 times per day. Americans are not only snacking more frequently but in larger quantities as Cutler, Glaeser, and Shapiro (2003) find that "...between 1977/78 and 1994/96 men and women nearly doubled the amount of calories consumed between meals. Men increased their between meal consumption by 240 calories; women increased their between meal consumption by 159 calories ... the increase in snack food calories more than compensates for the slight decline in calories consumed at dinner and far exceeds the slight increases in calories consumed at breakfast and dinner." By analyzing household-level snack food purchase data, we explain at least one potential source of this trend as well as consumers' tendency to substitute among alternative snack foods, based on differences in their content of key dietary nutrients.

Using the matrix of own- and cross-price elasticities estimated with the RCL model, we also simulate changes in total nutrient consumption based on product-specific "sin taxes." Such taxes have been advocated in the past as

2. The Center for Disease Control and Prevention (2004) defines obesity as a body mass index (BMI) of over 30.0. BMI is defined as weight (in kg) divided by height (in m) squared. A BMI value over 40.0 is defined as "morbidly obese."

potentially effective ways to reduce the consumption of specific foods deemed to be particularly unhealthy. However, advocates of sin taxes rarely consider the likely response of consumers given the wide variety of snack foods available to them. The results of our simulation are hardly surprising. In fact, targeted product-level taxes are not likely to achieve their nutritional goals as consumers tend to switch relatively easily from one food to another, sometimes increasing the amount of harmful nutrients purchased.

The results of this study are important for both policy makers and health care industry members as they provide critical information as to possible policy responses that may prove valuable in combating the obesity epidemic. Typically, the insight provided by the rational addiction literature maintains that if a product is found be addictive in an economic sense, then tax policies, which raise consumer expectations of future prices, may be more effective in reducing demand than previously believed. However, if the addiction is to an ingredient rather than the product itself, then tax policy targeted toward products and not ingredients may, in fact, be less effective than expected. In the next section, we describe the rational addiction model and its implications. The third section presents a new econometric model of the rational addiction hypothesis that overcomes many limitations of prior tests of the rational addiction theory, while the fourth describes the household panel data set that is used in estimating the model. A fifth section presents the estimation results, both from testing the primary addiction hypotheses and the structure of demand for snack foods. This section also describes the simulation exercise and provides an interpretation of the implications for antiobesity policy. The final section concludes and provides a discussion of limitations and possible directions for future research in this area.

II. AN ECONOMIC MODEL OF NUTRIENT ADDICTION

Although satiation is a physiological concept, Mela and Rogers (1998) cite psychological reasons why people eat beyond the point of biological optimality. Cawley (1999), on the other hand, considers obesity the result of an addiction to calories. Wang et al. (2004) provide clinical support for this hypothesis through positron emission tomography scans of 12 obese sample subjects. Specifically, this experiment found that brain responses among obese individuals when presented with external food stimuli were similar to that found among cocaine addicts when given doses of the drug. Nutrition research, however, suggests that dependencies are rather associated with the unique chemical compositions of particular nutrients, such as fats or simple sugars (Colantuoni et al., 2002). Therefore, this study follows Cawley (1999) but extends his analysis by investigating whether addiction can be attributed to a specific nutrient or set of nutrients.

In terms of the rational addiction model of Becker and Murphy (1988), individuals weigh the current benefit of increased current utility from eating, which is assumed to be inherently enjoyable, to the present value of future health implications from overeating. To be a rational addiction, as opposed to myopic, or merely habitual behavior, Becker and Murphy (1988) argue that an individual's utility from consuming food must exhibit two characteristics: (1) reinforcement, in which current marginal utility rises in the stock of past consumption; and (2) tolerance, in which the individual must consume more of the addictive product in order to maintain the same level of utility, the higher is past consumption. This concept of addiction has met with considerable criticism, however, in that it implies that addicts are somehow "happy" with their situation and would not change it if they could. Suranovic, Goldfarb, and Leonard (1999), on the other hand, develop a model of addiction in which adjustment (withdrawal) costs prevent an addict from reducing consumption below harmful levels, while Winston (1980) develops a theoretical explanation for how former addicts can all too often "fall off the wagon" and resume their old behaviors. Similarly, Orphanides and Zervos (1995) explain how addicts can regret their current situation but are prevented from changing it due to the high costs of learning how to quit. These arguments are plausible when applied to examples such as cigarettes or alcohol, but they are even more convincing in the case of food because humans can avoid drinking or smoking but not eating. Although the rational addiction model has met broad acceptance in the economics field due to its agreement with fundamental principles of neoclassical economic analysis, others consider addictive behavior as the result of impulsive, "multiple-self" decisions (Schelling, 1978; Thaler and Shefrin, 1981), or hyperbolic discounting (treating the distant future as inconsequential) (Gruber and Koszegi, 2001) that essentially reject rationality as a cause of addiction. Nonetheless, the rational addiction model has met with considerable empirical success.

III. EMPIRICAL MODEL OF NUTRIENT ADDICTION

The primary empirical implication of the rational addiction model is that current consumption responds to not only current and past prices but expected future prices and consumption as well. Numerous empirical tests of the rational addiction model exist in the literature, examining addictions to cigarettes (Becker, Grossman, and Murphy, 1994; Chaloupka, 1991; Douglas, 1998; Keeler et al., 1993), alcohol (Grossman, Chaloupka, and Sirtalan, 1998; Waters and Sloan, 1995), cocaine (Grossman and Chaloupka, 1998), caffeine (Olekalns and Bardsley, 1996), heroin (Bretteville-Jensen, 1999), and calories from food (Cawley, 1999, 2000, 2001). These studies show near-uniform support for the rational addiction hypothesis, but in very simple, single-equation econometric models. To study the dietary source of obesity, however, it is necessary to account for the fact that "all calories are not equal" or that calories from different sources, fat, protein, and carbohydrate, may differ in their addictive properties and hence in their contribution to obesity.

Despite the empirical success of the rational addiction model, there are (at least) three primary reasons why existing empirical methods cannot be used to test for addiction to nutrients: (1) they are all based on single-product models of demand that do not allow for substitutes, (2) nutrients do not have observable prices, and (3) they impose severe restrictions on utility and hence on the resulting demand functions.[3] The first problem cannot be overcome by modeling the demand for all foods in a traditional demand system because consumers face too many food choices. We solve this problem by adopting the characteristic demand approach of Lancaster (1971) and BLP (1995) and project the demand for each food into the smaller set of nutrients and minerals (fat, protein, carbohydrates, and sodium). However, it is not possible to model substitution among nutrients directly as nutrient prices are unobservable. Fortunately, in the econometric approach described below, substitution among foods is driven by the implicit or shadow values of their attributes. The resulting demand estimates exhibit general patterns of substitution that are not estimable using more simple linear demand models.

As suggested above, the primary empirical problem in estimating addictiveness among particular foods is one of dimensionality, there are simply too many possible foods to hope to estimate a substitution matrix with any degree of confidence. Recent developments in the theory (Berry, 1994; McFadden and Train, 2000; Nevo, 2000) and application (BLP, 1995; Chintagunta, 1994; Chintagunta, Dube, and Singh, 2002; Nevo, 2001) of the RCL model provide a means of estimating substitute relationships among products by projecting their demand into characteristic space, thus greatly reducing the number of estimated parameters. Further, this approach also avoids the unrealistic restrictions on own- and cross-price response elasticities associated with fixed-coefficient logit demand models and does so in a parsimonious way. Because the data used in this study consist of household-level food choices, our model differs substantially from those referred to above. Nonetheless, we retain the key insight that substitution relationships among different food products are driven fundamentally by differences in their nutritional composition.

Formally, the RCL model is derived from a random utility framework. The utility consumer i obtains from consuming product j on purchase occasion t is a function of the product's price (p_{jt}) and mean level of utility, or product-specific preferences, γ_{ijt}, as well as a set of demographic variables (z_{il}):

$$(1) \qquad \mathrm{u}_{ijt} = \gamma_{ijt} + \alpha_i p_{ijt} + \sum_l \delta_l z_{il} + \varepsilon_{ijt},$$

where we assume the price-response coefficient is normally distributed so that $\alpha_i \sim N(\bar{\alpha}, \sigma_\alpha^2)$. Similar to Berry (1994), BLP (1995), and Erdem (1996), product-specific preferences depend on the attributes (nutrients, k) of each product, j:

3. For example, the cigarette-demand model of Becker, Grossman, and Murphy (1994) treats the demand for cigarettes in the current period (C_t) as a function of past (C_{t-1}) and future (C_{t+1}) consumption and prices (P_t) in a single-equation specification: $C_t = \theta C_{t-1} + \beta\theta C_{t+1} + \theta_1 P_t + \theta_2 e_t + \theta_3 e_{t+1}$, where the θ parameters are complex functions of the underlying structural parameters. The test for rational addiction concerns whether the parameter $\beta\theta$ is significantly different from zero.

$$(2) \qquad \gamma_{ijt} = \sum_k \beta_{ik} x_{jk}, \quad k = 1, 2, 3.$$

Consumers are assumed to differ in their preference for each nutrient so that unobserved consumer heterogeneity is reflected in the distribution of each nutrient's marginal utility:

$$(3) \quad \beta_{ik} = \beta_k + \mu_{ik} \mu_{ik} \sim N(0, \sigma_0^2), \quad \forall k = 1, 2, 3.$$

Brownstone and Train (1998) interpret the elements of Equation (3) in terms of an error-components model of attribute demand. In contrast to the IIA property of a simple logit model, the heterogeneity assumption in Equation (3) creates a general pattern of substitution over alternatives j through the unobserved, random part of the utility function given in Equation (1). The difference between a random coefficient and simple logit model is easily shown by expressing the partial covariance matrix of Equation (1) as

$$(4) \qquad E([\beta' x_j + \varepsilon_j][\beta' x_m + \varepsilon_m]) = x_j' V(\beta) x_m,$$

which is defined over the vector of nutrients, k, for each food choice. So alternative foods are correlated according to their nutritional profiles as described by the vector x_j. Allowing for non-IIA substitution among alternatives in this way is key to the objectives of this study because foods that are nutritionally similar should be close substitutes, regardless of their market share.

In this basic RCL framework, however, utility depends only on current consumption. Erdem (1996) introduces state-dependent preferences by allowing utility to reflect both habit persistence and variety-seeking behavior.[4] With this approach, utility depends on the "distance" of each attribute acquired during the current purchase occasion from the previous one. If utility rises with this distance, then the consumer is variety seeking, but if it falls, then the consumer is habituated. Because distance is measured only in a backward-looking way, habits described by this model are myopic and not forward looking, or rational. Therefore, we extend the dynamic utility model to consider forward-looking decisions. If consumers are rational in the sense of Becker and Murphy (1988) or Chaloupka (1991), then utility falls in the difference between current and future attribute purchases as well.[5] If this is the case, then the consumer may indeed be addicted to the attribute, or nutrient in question. To incorporate habituation, variety seeking, and addiction into the utility model, mean utility becomes:

$$(5) \quad \gamma_{ijt} = \sum_k \beta_{ik} x_{jk} - \sum_k \lambda_{ikl} (x_{jk} - \sum_j x_{jk} d_{i,j,t-1})^2 - \sum_k \lambda_{ik2} (x_{jk} - \sum_j x_{jkdi,j,t+1})^2,$$

where $d_{itj} = 1$ if consumer i buys product j at time t, and 0 otherwise; $\lambda_{ik1} > 0$ implies habit persistence; $\lambda_{ik1} < 0$, variety seeking behavior; and $\lambda_{ik2} > 0$ rational addiction. Because consumers are also assumed to be heterogeneous with respect to their preferences for deviations from past purchases, each λ_{ikm} is assumed to be given by $\lambda_{ikm} = \lambda_{km} + v_{ikm}, \quad v_{ikm} \sim N(0, \sigma_m^2)$, for $m = 1, 2$ and $k = 1, 2, 3$. Further, note that this model also captures the impact of adjustment costs on the likelihood that a consumer becomes addicted to a particular nutrient.[6] If $\lambda_{ik1} > 0$, then withdrawal symptoms or the psychological costs of denying a want cause utility to fall.

By defining the characteristics of foods consumed by a panel of individuals as those that are potentially addictive, fat, carbohydrate, protein, sodium, caffeine, for example, we are able to test not only whether foods are addictive or not but the source of their addiction. Further, this method is also able to account for the fact that individuals do not have similar tastes. By allowing consumer-specific heterogeneity, we are better able to estimate realistic own- and cross-price elasticities among products.

4. Unlike Chintagunta, Dube, and Singh (2002) or Erdem (1996), however, we incorporate observable measures of product attributes and not latent factors. In these previous studies, the objective was to elicit perceptual "market maps" and not to test for the responses to specific attributes. In this respect, our treatment of observed attributes is more akin to Brownstone and Train (1998).

5. Compare the λ_{ik2} parameter in this expression to the $\beta\theta$ parameter of Becker, Grossman, and Murphy (1994). While their interpretations differ, the implications are nonetheless the same. Namely, a reduction in future consumption reduces utility and hence demand in the current period.

6. In general, there are likely to be other interpretations for this parameter besides a rational addiction or adjustment costs. Clearly, we cannot suggest that failing to reject the null hypothesis that this parameter is equal to zero is proof of a rational addiction, only that we cannot rule it out.

This method also overcomes the failure of existing empirical models of rational addiction to consider the demand for multiple products that may convey the same addictive properties. Accounting for potential complementarities in demand will allow for an even richer description of the nature of addiction.

IV. DATA AND ESTIMATION

Estimating an RCL model requires data on prices, purchase quantities, and product characteristics, while data on consumer demographics is helpful but not necessary. While BLP (1995) and Nevo (2001) estimate RCL models in data representing differentiated products at an aggregate (U.S. market) level, this study uses household panel data for a number of different snack foods purchased at retail outlets. Specifically, we use A.C. Nielsen, Inc. "HomeScan" data in which participating households submit all food purchase information (price, quantity, product description) each time they visit any type of retail food outlet using remote scanning devices. The HomeScan database also includes a number of socioeconomic and demographic descriptors. For purposes of this study, we use all shopping trips over a 4-yr period (1998–2001) for a random sample of 30 households from a major Southeast market. Table 1A provides a summary of the demographic attributes of the sample households. Including all snack food purchases made over the 1998–2001 sample period, this sample provides over 5,155 total purchase observations.[7] Further, we focus on the snack food category because it is most likely to reveal either habitual or variety-seeking behavior. Indeed, the snack food category is ideal for the objectives of this study because snacks are commonly purchased on impulse, snacks can vary widely in terms of their nutritional profiles, and are likely to be purchased frequently and regularly. Further, as described above, excessive snacking is often blamed for the general rise in obesity among U.S. adults (Cutler, Glaeser, and Shapiro, 2003).

Nutritional profiles for each snack food are constructed from the USDA food guide database and aggregated according to sample weights from within the A.C. Nielsen data set. We use the A.C. Nielsen definition of what constitutes a "snack food" and augment this list with a number of others such as cookies and crackers. Table 1B provides a full listing of the chosen foods and some summary statistics regarding their purchase and nutritional content. In the RCL model, nutritional attributes of each food serve the dual role of defining the level of mean utility and the nature of all substitution relationships as foods that are nutritionally similar are likely to be highly correlated through the heterogeneity described in model (1). Because many households purchase several snack foods on each purchase occasion and do so in varying quantities, we define the dependent variable in terms of the share of total snack food expenditures attributable to each particular food. Estimating with shares is necessary in the RCL model and consistent with the approach taken by Berry (1994), Nevo (2000), and others. Implicitly, therefore, we estimate a version of the RCL in which we aggregate within each household over discrete "consumption occasions." In other words, purchase data reflect prior planning over many different snack times so the primative we model is the consumption occasion, although we only observe purchase occasions. Dube (2004) uses this insight as motivation for his model of "multiple discrete" carbonated soft drink purchases. Further, we do not standardize on a typical package size as is the case with most studies that also use panel data.[8]

7. For a comparison to other panel data studies that use a similar empirical approach, Erdem (1996) uses 2,212 total purchases, Jain, Vilcassim, and Chintagunta (1994) estimate with 2,509 purchases, and Chintagunta's (1994) sample consists of 4,377 separate purchase occasions. Note that, because the unit of observation is the "purchase occasion" or visit to the store, the sample contains a greater frequency of heavy snack food purchasers relative to light purchasers. While this means frequent purchasers have a greater influence on the resulting parameter estimates, we do not re-weight observations in the estimation procedure because our objective is to understand the behavior of these frequent purchasers. If addiction results in frequent store visits, then this should be reflected in the model estimates. We thank a reviewer for pointing this out.

8. Although addiction is commonly thought of as an individual behavioral trait, Becker, Grossman, and Murphy (1994), among others, estimate their models in aggregate data. Further, there is a rich history of specifying and estimating household-level models as if they reflect a single utility function. For example, in his paper on the opposite concept to addiction, variety seeking, Erdem (1996) explains that "...variety seeking can be defined at the aggregate level as the desire for variety without differentiating whether individual members are indeed variety seekers or the household at the aggregate is a variety seeker ..." As long as one addicted household member's demands are reflected in weekly purchases by a household, the household's behavior will exhibit addictive tendencies.

TABLE 1A
Summary Statistics, Major Southeast Market, A.C. Nielsen HomeScan, 1998–2001

Variable[a]	Mean	Standard Deviation	Minimum	Maximum	N
Household Size	2.91	1.50	1.00	8.00	30
Household Income	\$54.47	\$23.67	\$17.50	\$100.00	30
Age of Household Head	6.91	2.19	3.00	9.00	30
Children	0.39	0.49	0.00	1.00	30
Education Level of Household Head	4.65	0.81	3.00	6.00	30
Race	1.11	0.32	1.00	2.00	30
Number of Purchases	179.51	62.04	31.00	317.00	30

[a]Variables are defined as follows: Household Size is number of residents of any age; household income is income in \$,000.00; Age of Household Head is categorical where 1 = 0–25 yr, 2 = 25–29 yr, . . ., 9 = 65+ yr; Children is a binary variable where 1 = children and 0 = no children; Education Level is categorical where 1 = grade school, 2 = some high school, . . ., 6 = postgraduate degree; Race is a categorical variable where 1 = white, 2 = black, 3 = oriental, and 4 = other; and Number of Purchases is the number of unique snack food purchase occasions over the sample period.

Assuming the error term in Equation (1) is type I extreme-value distributed, we estimate the complete RCL model using maximum likelihood.[9] With this error assumption, the probability of an individual household i purchasing product j on occasion t is given by

$$(6) \qquad P(f=1) = \frac{e^{\gamma_{ift}+\alpha_i p_{ift}+\sum_l \delta_i z_{il}}}{\sum_j e^{\gamma_{ijt}+\alpha_i p_{ijt}+\sum_l \delta_i z_{il}}},$$

where utility from one of the $j = 1, 2, 3, \ldots m$ foods is normalized to zero in order to facilitate estimation. It is widely understood in the literature that estimation of Equation (6) requires the evaluation of multiple integrals, one for each source of heterogeneity that is assumed. Consequently, there is no closed-form solution for the maximization procedure proposed in Equation (6). To address this problem, we follow the literature by estimating the RCL model using the method of simulated maximum likelihood (MSL), which involves drawing random samples from each of the heterogeneity distributions, evaluating the resulting likelihood function at each draw, and maximizing over the distribution of joint outcomes. The simulated likelihood function for this procedure is as follows:

$$(7) \quad \log L(x_y, p_y, z_y | \Theta) = \sum_{i=1}^{N}\sum_{t=1}^{T} \log \frac{1}{R}\left(\sum_{r=1}^{R} \frac{e^{\gamma_{iftr}+\alpha_i p_{ift}+\sum_l \delta_i z_{il}}}{\sum_j e^{\gamma_{ijtr}+\alpha_i p_{ijt}+\sum_l \delta_i z_{il}}}\right),$$

for the set of parameters $\Theta = (\gamma, \alpha, \delta, \beta, \lambda)$, defined over N panel members, with T purchase occasions each and R draws from the random distributions that define the parameters that comprise mean utility, γ_{ijt}.[10] Alternatives to this method include the method of simulated moments. Nevo (2001) discusses the relative merits of this method compared to MSL. Hypotheses to be tested with the estimates include the significance of all own- and cross-price elasticities in addition to the core rational addiction hypotheses. In this regard,

9. Note that Equation (1) does not include the product-specific error term, ξ_j, described in Berry (1994), BLP (1995), Chintagunta, Dube, and Singh (2002), and Nevo (2000, 2001). With their approach, this error term captures all attributes of the product that are unobserved to the econometrician but likely to be correlated with the price. In a retail environment, such attributes may include shelf placing, coupon usage, stock levels, or a host of other factors. If these are important, then prices are endogenous and the instrumental variables procedure described by Berry (1994) must be used. In our application, however, it is plausible that prices are instead exogenous, as is commonly assumed in similar studies using panel data (Chintagunta, 1994, for example). In future research, however, we incorporate a test for endogeneity in these panel data.

10. We do not include an outside option in the utility specification because calculation of a nutritional profile for nonsnack foods (the logical choice) was infeasible. Note that by not including an outside option, the RCL model does not allow for category expansion over time but focuses instead on the allocation of snack food spending among products with different nutritional composition. This is appropriate given the objectives of the study.

TABLE 1B
Summary Statistics of Snack Food Nutrient Contents

Food	Share	Amount (100 g)	Energy[a] (Kcal)	Fat (g)	Protein (g)	Carbohydrate (g)	Sodium (mg)
Popcorn	0.044	0.614	500.345	28.101	9.124	57.223	884.532
Corn chips	0.036	0.238	536.453	33.289	6.664	56.789	651.172
Low-fat potato chips	0.022	0.101	432.336	12.311	8.167	73.986	555.460
Regular potato chips	0.160	0.880	526.508	34.053	7.341	52.613	624.714
Pretzels	0.030	0.244	388.902	4.830	9.030	78.200	1621.304
Puffed cheese	0.029	0.153	552.524	34.130	7.611	54.024	1052.843
Tortilla chips	0.053	0.375	495.077	25.110	7.431	63.415	596.925
Pork rinds	0.005	0.018	542.157	31.503	59.919	0.650	2174.663
Snack meats	0.005	0.007	331.409	26.651	17.891	4.119	1345.295
Cookies	0.264	2.240	466.820	20.860	5.220	66.820	409.310
Crackers	0.121	1.058	476.974	20.284	8.714	64.232	1051.400
Nuts	0.072	0.606	595.879	52.198	19.253	22.675	508.776
Carrots	0.088	1.827	52.196	0.170	0.260	13.810	1.094
Apples	0.071	0.884	145.392	0.130	0.640	8.243	78.221

[a]In this table, all nutrient contents are given on a per 100 g basis.

rational addiction involves the parameters of the mean utility function. Because our objective concerns the addictiveness of individual nutrients, we test for rational addiction using t-tests for each nutrient as opposed to a joint test of all nutrient dynamics together. The results of this testing procedure are presented in the next section.

V. RESULTS AND DISCUSSION

Before interpreting the parameters of the RCL model, it is first necessary to establish the validity of this estimation approach relative to simpler alternatives. Because the RCL model is a generalization of a nonrandom coefficient discrete choice approach, the most direct test between these two alternatives involves comparing the log-likelihood function value of the estimated, random coefficient model with one in which all parameters are held constant. Using the log-likelihood values reported in Table 2, a likelihood ratio test statistic for the null hypothesis that all coefficients are constant is 4,517.01, while the critical value for 5 degrees of freedom at a 5% level of significance is 11.07. Therefore, we are led to reject the null hypothesis and conclude that the RCL represents a better description of the household scanner data than a constant coefficient logit model. A second set of specification tests examine the statistical significance of the standard deviations for each of the maintained random coefficients in Table 2 using standard *t*-test statistics. According to this approach, it is evident that all the random parameters have standard deviations that are significantly different from zero.[11] Therefore, the RCL approach again represents a better description of the underlying data than a constant-parameter alternative.

In the RCL model, each food is defined in terms of its attributes, including both price and nutrient content. Therefore, the parameter estimates presented in Table 2 show the sample-average (latent, or unobserved) marginal utility associated with variations in price, each nutrient, and the lagged and lead nutrient distance measures defined above. For example, in Table 2, the coefficient of 0.045 on the "protein" variable suggests that the implicit marginal value of protein for the average consumer in the data is 0.045 per gram. Similarly, the "product preference" parameters show the average consumer's strength of preference for each product relative to the average in the data set. From the results in Table 2, it is apparent that consumers have a strong preference for cookies and a relative aversion to pork rinds.

11. Although the empirical model description above included random product preference and nutrient-distance weights as well, this more general model would not converge in a meaningful way. Therefore, the final model includes only price-response and nutrient-distance heterogeneity.

TABLE 2
Demand for Snack Foods: Random-Coefficients Logit Model Parameter Estimates, Simulated Maximum Likelihood

Utility Parameters			**Product Preferences**											
				Constant		**Household Size**		**Household Income**		**Random Coefficient Standard Deviation**			**Model Statistics**	
	Estimate	**t-Ratio**		**Estimate**	**t-Ratio**	**Estimate**	**t-Ratio**	**Estimate**	**t-Ratio**					
Price[a]	−0.273	−127.548	Popcorn	0.737	2.211	−0.854	−7.024	−0.029	−3.144	Price	0.017	2.367	N	5,155
Protein	0.045	7.073	Corn chips	−0.843	−3.510	−0.054	−0.438	0.042	5.162	Protein	0.126	64.387	LLF	−6,431.661
Fat	−0.010	−4.911	Low-fat potato chips	−0.652	−2.245	−0.068	−0.593	0.053	7.600	Fat	0.033	81.814	LLF (const parameters)	−8,690.165
Carbohydrate	0.010	21.367	Puffed cheese	1.140	3.270	−0.147	−2.133	0.041	8.854	Carbohydrates	0.004	19.871	LLF (null model)	−13,604.328
Sodium	0.007	2.510	Tortilla chips	−0.719	−4.212	−0.297	−2.059	−0.016	−1.789	Sodium	0.001	52.953		
$^{-}\Delta$Protein	3.504	4.311	Regular potato chips	−0.337	−2.607	−0.200	−1.589	0.025	2.924					
$^{-}\Delta$Fat	5.475	4.210	Pretzels	−0.176	−7.368	−0.225	−2.264	0.039	5.537					
$^{-}\Delta$Carbohydrates	7.914	16.601	Pork rinds	−1.936	−4.795	0.092	0.104	0.006	0.151					
$^{-}\Delta$Sodium	−0.001	−0.805	Snack meats	−0.625	−3.018	−0.910	−3.177	0.086	6.078					
$^{+}\Delta$Protein	1.042	2.502	Cookies	1.246	3.730	−0.280	−4.308	0.020	4.426					
$^{+}\Delta$Fat	6.019	4.329	Crackers	−0.185	−4.466	−0.085	−1.140	0.026	4.595					
$^{+}\Delta$Carbohydrates	8.813	10.175	Nuts	−0.195	−2.406	−0.051	−0.425	0.045	6.066					
$^{+}\Delta$Sodium	−0.004	−2.787	Apples	0.673	5.714	−0.079	−1.023	0.014	2.388					

Note: LLF, log-likelihood function.
[a]In this table, all parameters but the standard deviations for fat and carbohydrates are significant at a 5% level. For each nutrient deviation, $^{-}\Delta$ indicates the difference between the implicit quantity purchased on this occasion relative to the previous occasion, while $^{+}\Delta$ is the difference between the current occasion and the next. A chi-square test statistic comparing the null and estimated models consists of 73 degrees of freedom, so the critical value is 90.53 at a 5% level. The chi-square test statistic is calculated as twice the difference between the estimated and null (all coefficients restricted to zero) log-likelihood function values.

This is consistent with prior expectations. Interestingly, at current consumption levels, the marginal utility associated with fat content is negative. In the terminology of Becker and Murphy (1988), this suggests that, if found to be addictive, fat constitutes a "harmful addiction."

Whether or not each nutrient can indeed be defined as addictive in the sense of Becker and Murphy (1988) involves examining the sign and significance of each of the nutrient distance measures. As defined by Erdem (1996), a positive "habit persistence" parameter suggests that the average household consumes the nutrient in a habitual way. If this parameter is negative, then households are more prone to variety seeking because their utility rises, the more dissimilar the current purchase is from the last. From the lagged-distance parameter estimates in Table 2, it is apparent that consumers tend to purchase snack foods that are relatively similar from one shopping trip to the next, except with respect to their sodium content. Although the lagged-distance parameter is not significantly different from zero, consumers obtain higher utility from consuming low-sodium snacks, ceteris paribus, if they expect the next to be salty. This result is interesting in that the other food attributes are all macronutrients, the consumption of which provides food energy, while sodium conveys taste and supports essential metabolic functions within the body. Therefore, if energy is a primary human need that drives addiction, then the demand for salt may indeed be more of a "want" than a "need." Finding that consumers tend to form habits in their food purchases is not new (Heien and Durham, 1991), but isolating a possible cause in nutritional dependence is. Habits, however, may reflect myopic decision making rather than rational, forward-looking addiction if there is not further evidence that consumers consider future consumption plans when deciding what to purchase today.

In fact, the rational addiction model implies that the "habit formation" parameter, or the parameter on the lead distance measure, is positive and significant for households that are not merely myopically habitual consumers of a particular nutrient, but form habits in a rational, forward-looking way. In other words, they are rationally addicted. According to the estimates in Table 2, the distance weight on each future nutrient value is positive and significant (again, with the exception of sodium), which suggests that consumers are indeed rationally addicted to each of the macronutrients considered here. Because the same general conclusion applies to all nutrients, the relative magnitude of each parameter is a better measure of a nutrient's comparative addictiveness. By this reasoning, the results in Table 2 show that protein is the least addictive of all nutrients followed by fats, while carbohydrates are slightly more addictive than the others. Consequently, despite the fact that much media attention and public debate has centered on "high-fat" fast food as a likely culprit in the obesity epidemic, our finding suggests a focus rather on increased consumption of high-carbohydrate foods. Drawing such a conclusion would be questionable if there were only marginal differences in the nutrient content of the foods included in the model. However, our analysis considers snack foods, a category that includes intensive sources of dietary fat (potato chips) as well as others that are very high in carbohydrate (pretzels, cookies) and protein (snack meats).

If consumers are indeed addicted to specific nutrients, but their addiction is part of a rational, dynamic utility maximization process in the sense of Becker and Murphy (1988), then this suggests that conventional economic tools (price-based taxes or subsidies) can be effective in modifying behavior. However, because foods are ultimately the medium by which consumers obtain nutrients, the effectiveness of any price-based policy depends on the preferences and price elasticities of demand for specific foods. The value of the RCL method in this regard lies in the fact that food elasticities are driven by their nutritional profiles and relative preference orderings are estimated directly from the data. Therefore, the information demands of policy makers or public health officials are directly reflected in the econometric method used here. In other words, when considering ways to ameliorate any nutrient-addictive behavior that may contribute to obesity, policy makers or public health officials are equally as interested in the structure of the demand for the products that deliver nutrients (i.e., foods) as they are with the demand for nutrients themselves.

Results concerning the intensity and observed heterogeneity of demand, as determined by households' demographic characteristics, are provided in Table 2 and the matrix of demand

TABLE 3
Snack Food Own-Price and Cross-Price Elasticities[a]

	PPC	CCH	RFPC	RPC	PTZ	PFC	TTC	PKR	SNM	COK	CRK	NTS	APP	CAR
PPC	−1.653	0.099	0.161	0.422	0.027	0.049	0.113	0.003	0.018	0.231	0.124	0.138	0.196	0.072
CCH	0.011	−2.179	0.143	0.429	0.013	0.049	0.114	0.003	0.016	0.245	0.119	0.140	0.203	0.074
RFPC	0.019	0.103	−2.971	0.437	0.025	0.050	0.118	0.003	0.013	0.246	0.117	0.145	0.206	0.083
RPC	0.015	0.086	0.121	−1.779	0.011	0.042	0.102	0.003	0.008	0.265	0.109	0.122	0.176	0.063
PTZ	0.022	0.101	0.147	0.427	−1.363	0.049	0.116	0.005	0.019	0.241	0.115	0.142	0.201	0.094
PFC	0.019	0.102	0.146	0.431	0.012	−2.005	0.116	0.003	0.014	0.247	0.116	0.141	0.203	0.074
TTC	0.011	0.100	0.142	0.423	0.090	0.048	−1.999	0.003	0.009	0.245	0.114	0.139	0.199	0.073
PKR	0.009	0.102	0.149	0.433	0.011	0.050	0.117	−5.061	0.023	0.234	0.111	0.141	0.194	0.075
SNM	0.005	0.082	0.123	0.344	0.008	0.039	0.090	0.001	−5.011	0.176	0.078	0.106	0.152	0.056
COK	0.012	0.081	0.115	0.360	0.010	0.040	0.096	0.003	0.008	−1.566	0.108	0.113	0.164	0.059
CRK	0.013	0.091	0.130	0.392	0.012	0.045	0.105	0.003	0.016	0.240	−1.681	0.130	0.180	0.067
NTS	0.019	0.094	0.135	0.399	0.011	0.046	0.107	0.003	0.012	0.236	0.102	−2.700	0.190	0.070
APP	0.021	0.105	0.151	0.321	0.023	0.056	0.131	0.003	0.003	0.218	0.134	0.154	−0.766	0.091
CAR	0.024	0.104	0.151	0.314	0.031	0.059	0.121	0.003	0.005	0.204	0.131	0.161	0.281	−0.752

[a]In this table, each column represents the elasticity of the column product with respect to the price of the row product. Elasticity values are sample averages. All elasticities are significant at a 5% level. The variables are defined as follows: PPC = popcorn, CCH = corn chips, RFPC = reduced-fat potato chips, RPC = regular potato chips, PTZ = pretzels, PFC = puffed cheese, TTC = tortilla chips, PKR = pork rinds, SNM = snack meat, COK = cookies, CRK = crackers, NTS = nuts, APP = apples, CAR = carrots.

elasticities in Table 3. Although there are many other household traits that may influence snack food demand, income and household size were considered the most important. Because snack foods vary greatly in price, lower income households are not able to afford many of the snacks purchased by those with higher incomes. Holding income constant, larger households are likely to have more children, so household size is an important proxy for variations in taste driven by age variation. Defining carrots as the numeraire commodity, Table 2 shows that the sample households express a preference for cookies, puffed cheese, and apples, while they show a comparative dislike for products such as pork rinds, corn chips, and tortilla chips. Holding mean preferences constant, these results also show that larger households have a relative dislike for popcorn and snack meats, while, perhaps surprisingly, favoring no other snack foods to carrots in a statistically significant way. Higher income households, on the other hand, appear to prefer snack meats, low-fat potato chips, nuts, corn chips, and puffed cheese while showing less of a preference for popcorn and tortilla chips. In terms of other "healthy" snacks, apple preferences rise only slightly in income relative to the other products. Combining these two results, it appears as though rising incomes may not increase the demand for the most healthy snacks (fruit), but it is associated with a preference for some foods that are consistent with current popular diets (Atkins, South Beach, or traditional low fat).

As suggested above, any consumption-based response to the obesity epidemic is likely to address specific foods or classes of foods rather than specific nutrients. Therefore, the structure of snack food demand may become of considerable practical importance. To this end, we present the matrix of own- and cross-price elasticities in Table 3. Before interpreting individual elasticity estimates, it is important to provide some observations on the value of the RCL approach. In fact, these estimates demonstrate the true value of using an RCL approach relative to a continuous alternative such as an AIDS or a Rotterdam model. First, continuous alternatives are not likely to be able to provide precise, plausible elasticity estimates in a high-dimensional problem such as this. Second, while continuous demand models often produce seemingly anomalistic cross-price elasticity estimates, the results in this table indicate that all products are gross substitutes for each other, a highly plausible outcome in a category of largely discretionary, or impulse purchases. Third, because the cross-price elasticities are driven by correlations among random nutrient marginal utilities, products that are "similar" to each other in a nutritional sense represent closer substitutes than those that are fundamentally different products. For example, it is very plausible to expect popcorn and pretzels to be close substitutes, while popcorn and pork rinds are likely to satisfy quite different needs. Further, the two fresh produce snacks are closer substitutes for each other and similar low-fat alternatives such as reduced-fat potato chips and pretzels rather than more fatty snacks. More importantly, apples and carrots are also the only two snacks that are inelastic in demand, while the two meat-based snacks are far more elastic than the other foods. This suggests that any tax applied to snack meats or pork rinds is likely to significantly reduce consumption, while efforts to increase fruit and vegetable snacking through price-based policies is likely to be ineffective. Moreover, regular potato chips are significantly less elastic in demand than reduced-fat alternatives so any "sin tax" that targets "potato chips" in an indiscriminate way is likely to alter consumption toward the high-fat option. Rather, if the desire is to reduce the intake of foods high in addictive content, then taxes should be targeted more toward corn chips, puffed cheese, and tortilla chips, each of which is relatively elastic and carbohydrate dense. In any case, the ultimate impact of a targeted tax is an empirical question as the impact of a new tax on net nutrient consumption depends on the nutrient content of both taxed and untaxed foods and the cross-price elasticities of demand.

Fortunately, the estimates shown in Tables 2 and 3 are ideally suited for this purpose. In order to simulate the impact of a set of targeted, product-level taxes intended to change the consumption-specific nutrients, we focus on three products from the list presented in Table 1B: nuts, pretzels, and regular-fat potato chips. By choosing this set of products, we simulate the impact of a tax targeted toward a high-fat product, a high-carbohydrate product, and one that is typically singled out in the media as a likely target for a junk food tax in general, respectively. Assuming no short-run supply response from tax food manufacturers,

TABLE 4
Simulated Policy Impacts on Nutrient Consumption: 10% Tax, Zero Supply Elasticity

	10% Tax on:		
Nutrient[a]	**Pretzel**	**Nuts**	**Regular-Fat Potato Chips**
Calories (per year)	2,301.83	−1,867.59	−1,699.79
Fat (g per year)	144.51	−258.77	−145.32
Protein (g per year)	27.97	−109.26	−23.18
Carbohydrates (g per year)	232.28	157.13	−103.86
Sodium (mg per year)	741.34	−940.83	−2,284.53

[a]All nutrient values are expressed on a per-household basis. Because the average household consists of 2.91 individuals, dividing by this value gives the incremental value per household member. An additional 3,500 calories above minimum requirements will produce 1.0 pound of bodyfat.

the entire incidence of the tax falls on consumers, so prices rise proportionate to the tax (this assumption is also made by Cutler, Glaeser, and Shapiro, 2003). The results of this simulation are shown in Table 4. Clearly, a tax targeted toward specific foods high in a particular nutrient may, in fact, thwart the intent of the policy if the cross-price elasticity of demand is sufficiently high. In fact, a tax on pretzels not only fails to reduce carbohydrate consumption as intended but raises total fat and calorie intake. Taxing nuts, on the other hand, has the desired effect of reducing fat but causes net carbohydrate consumption to rise. Because regular-fat potato chips represent a relatively large budget-share item with few close substitutes, taxing them reduces the consumption of all component nutrients and minerals, as desired. Nonetheless, because each snack food represents a relatively small share of total purchases, the welfare, and body mass, impacts of a tax are likely to be small, on the order of one half pound of bodyfat per year per household.[12]

Fortunately, policy makers have other options besides taxes in order to achieve nutritional goals. Some of these tools may be better designed if nutrient-specific addiction were taken into account. In fact, given that our results show consumers to be addicted to carbohydrates to a greater extent than to fats or protein, then existing USDA dietary guidelines, as outlined in the controversial "food pyramid," may need to be modified somewhat. Rather than emphasizing limited consumption of fats and oils, perhaps a more effective strategy to stem the obesity epidemic should recommend limiting carbohydrate intake. This recommendation would also be consistent with current trends in the weight-loss industry wherein low-carbohydrate diets such as Atkins and South Beach are becoming increasingly popular. While proponents of these diets have sought scientific support for their validity in the nutritional science literature, this study provides at least indirect support from the economic analysis of consumption data. More importantly, finding that both nutrients often associated with overconsumption and obesity, fats and carbohydrates, can be addictive suggests public policy oriented toward controlling obesity should be directed at the addiction and not necessarily current consumption. Because addicted consumers do indeed take the future economic implications of their behavior into account, price-based policies may be more effective than previous behavior-based models of obesity would have led us to believe.

Our findings also have important implications for producers of apparently less-addictive commodities, such as fruits and vegetables or even protein-dense meats and dairy products. For retailers or commodity groups charged with marketing these products, the optimal marketing solution may not lie in price promotion or discounting as is appears to be with the rationally addictive products, but rather advertising or public relations. If fresh produce is indeed on the "wrong side" of an addictive process that is based in otherwise rational, price-based economic decision making, then continued investment in information and advertising programs that emphasize the sweetness and flavor of fresh snacks may be more successful. Price promotion, discounting, or

12. Consumption of 3,500 calories above basic requirements leads to one pound of additional bodyfat.

couponing may be effective in changing the demand for high-fat and high-carbohydrate snacks, but discounting produce is not likely to change the forward-looking, cost-benefit calculus that drives addictive behaviors.

VI. CONCLUSIONS

This study provides a test of the rational addiction hypothesis as a potential explanation for the current "obesity epidemic." Because calorie expenditure among Americans has been relatively static over the past 20 yr, while calorie consumption has risen dramatically, obesity is now widely believed to be predominantly a consumption phenomenon. Addiction to food, or more precisely the most harmful macronutrients in food, presents a logical explanation for why consumers persist in purchasing and consuming more food than is necessary for survival.

Our test considers potential addiction to three macronutrients and one key mineral, fat, protein, carbohydrates, and sodium, in the case of snack foods purchased from retail outlets. Due to the large number of snack foods available to consumers, the demand estimation problem is made tractable through the use of RCL model in which the coefficients on each price and nutrient attribute are allowed to vary. In this way, we not only reduce the dimensionality of the problem but solve the IIA criticism of logit demand estimation by allowing the correlation among demand errors to be driven by nutrient content. The RCL model is applied to a highly detailed, disaggregate household panel scanner data set gathered by the A.C. Nielsen, Inc. (HomeScan) for 30 households over 4 yr in a major Southeastern metropolitan market.

The estimation results provide broad support for the rational addiction hypothesis for each macronutrient. Clearly, with a small sample of 30 households, our results are not intended to be generalizable to the broader population, but they do suggest that testing for rationally addictive behavior is possible in a randomly chosen sample of households. Based on this sample of households, it is also apparent that the addiction to carbohydrates is far stronger than to other nutrients. Importantly, the form of addiction in this model is an inherently rational one, so consumers purchase (and presumably consume) nutrients in amounts that are likely harmful to their health only through a reasoned process of comparing current marginal utility to the discounted future costs of any negative health consequences. Because consumers take costs and benefits into account and do not overeat out of some pathological obsession, price-based policies designed to address the obesity epidemic are likely to be more effective than once thought to be the case. Consequently, existing information-based policies may need to be rethought and "sin taxes" considered anew.

Simulations of possible sin-tax scenarios, however, demonstrate the importance in designing the tax and targeting nutrients, and not specific foods. For example, a 10% tax on pretzels, a high-carbohydrate snack, actually causes carbohydrate, fat, and protein consumption to rise due to the strength of the substitute relationships among snack foods. If consumers are indeed addicted to specific nutrients, and not foods, then taxes will simply cause them to find another source and not solve the problem as intended.

Given the importance of this issue to the U.S. economy, there are many avenues for future research efforts in this area. With respect to the method used here, additional research that uses a larger sample, or one from a different geographic region, may provide further insights, or corroboration for our results. More importantly, however, the potential addictiveness of snack foods suggests that other types of food may be addictive as well, fast food, candy, or beverages to name a few. Finally, there is a limited amount of research that shows how addictiveness may contribute to market power. Empirical investigation of this issue is of critical importance as lawsuits or any proposed legislation progresses in the future.

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